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The productivity impact of climate change: Evidence from Australia's Millennium drought

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ABSTRACT

The economic impact of climate change has usually been estimated based on changes in average weather condition and is often measured in terms of immediate loss of output or profit. Yet little is known about the impact of extreme weather event, in particular its impact on productivity in the medium to long term. Using Australia's Millennium drought as a case of extreme weather event and applying the synthetic control method, we show that severe droughts occurred between 2002 and 2010 has brought down agricultural total factor productivity by about 18 percent in Australia over the period, contributing significantly to the country's long-term slowdown of agricultural total factor productivity growth. Our results highlight the significance of productivity impact of extreme weather events that has been overlooked when accessing the economic impact of climate change.

1. Introduction

As global temperature rises, so is rapidly growing attention paid to the climate-economy relationship. Important as Tol (2009, p. 29) put it, “Climate change is the mother of all externalities: larger, more complex, and more uncertain than any other environmental problem”. With global warming and more frequent extreme weather shocks to be expected in the near future, a deeper understanding of the economic impact of climate change constitutes an essential step towards effective policy responses and institution arrangement (Dell et al., 2009).

In the literature, economic costs of climate change have usually been estimated for the loss of *current output* from the impact of changes in *average temperature and precipitation*. For example, Dell et al. (2012) show that temperature in a given year being 1 °C warmer leads to a fall of per capita income by 1.4 percent, but only in poor countries. In a report on the US economic impact of climate change (Ruth et al., 2007), the economic impact is estimated on the basis of current output loss due to forest fire, flooding, drought and increased sea level, among others. The Stern Review on *the Economics of Climate Change* shows that “using the results from formal economic models, the Review estimates that if we don't act, the overall costs and risks of climate change will be equivalent to losing at least 5 percent of global GDP each year, now and forever” (Stern, 2007, page vi). Garnaut (2008, 2011) provides excellent discussions on a severe and costly impact of climate change on agriculture, infrastructure, biodiversity and ecosystems in Australia. Most of these studies build on the assumption of the Solow (1956) model or the infinite horizon Ramsey-Cass-Koopmans model where long-run growth is derived from exogenous technological progress for which climate change does not have an impact.

However, an emerging body of empirical evidence suggests that extreme climatic shocks could have more severe on long-run productivity growth (Stern, 2013; Dietz and Stern, 2015). In fact, it is productivity that is at the heart of economic sustainability. The productivity impact of climate change may easily overwhelm contemporaneous output loss. It is possible that countries experiencing extreme climate conditions such as severe droughts may suffer from long term decline in agricultural productivity, beyond its effects of short-term output losses. First, severe droughts reduce profits and thus impose budget constraints on farmers to invest in advanced production techniques, leading to secular decline in productivity. Second, due to the nature of agriculture and farming practices, agricultural productivity is strongly influenced by farmers' expectation of the long-term climate condition. Change in expectation of future precipitation (due to droughts, for example) may lead to adjustments in farming practices and thus impact productivity. Third, unexpected droughts lead to year-to-year variability of precipitation and temperature, which expose farmers to greater production risks thus imposing negative impact on productivity. Historically, many of the largest falls in crop productivity have been attributed to anomalously low

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precipitation events (Kumar et al., 2004; Sivakumar et al., 2005). Of course, droughts may not always be bad for agricultural productivity growth at the industry level. Under certain circumstances, droughts may even affect productivity positively, for example, by reallocating resources from low efficiency farms to pioneer farmers who better use risk management and have higher productivity. This reallocation of resources may have positive impact on industrial productivity.

The Millennium drought in Australia represents an ideal case to study the productivity impact of climate change. First, it is a major weather shock. Between 2002 and 2010, Australia experienced one of the three most serious droughts on record — the Millennium drought. The Millennium drought differs from the previous two in history, the Federation Drought from 1895 to 1902 and the World War Two (WWII) drought from 1937 to 1945, in that it affected almost all regions along Australia's most agricultural production zones, i.e. the Murray-Darling River Basin and the southwest wheat belt (Heberger, 2012). Second, the Millennium drought affects Australia only but not elsewhere in the world. This makes it possible to identify its impact by using other regions of the world similar to Australia to be donor pool. Third, the shock results in substantial short-term output loss and possibly long term productivity decline. Some estimated that the Millennium drought leads to a loss of approximately half of all agricultural output between 2002 and 2010 when the same input was used.[1] Moreover, there are concerns that Australia's Millennium drought may have had negative impacts on its long-term agricultural productivity growth. Between 1996 and 2014, agricultural total factor productivity in Australia has grown at 0.7 percent a year, which is less than half of its historical trend over the period 1950 to 1996, i.e., 2.3 percent a year (Sheng et al., 2017). In terms of cross-country comparison, the growth of agricultural total factor productivity for Australia between 1996 and 2010 was 0.3 percent a year, which is much lower than that for OECD countries (1.7 percent a year) and for the world as a whole (1.4 percent a year) (Fuglie and Rada, 2013). As a consequence, the gap in agricultural productivity between Australia and its major competitors including the United States and Canada widens in recent decade.

However, there are challenges in correctly identifying the productivity impact of the Millennium drought since drought could interact with other agricultural productivity determinants that also impact on agricultural productivity. Specifically, we observe the "treatment effect", the actual productivity "*with intervention factor*", i.e. the Millennium drought. But we do not observe the counterfactual, the productivity "*without intervention factor*", a "drought-free" productivity. To identify the true productivity impact of the Millennium drought, we need to construct a "counterfactual" which is not "treated" (does not receive the "intervening factor"). This paper uses a newly developed technique, the synthetic control method, proposed by Abadie and Gardeazabal (2003) and further developed in Abadie et al. (2010) and Abadie et al. (2015), to construct a *synthetic* Australia by using selected "drought-free" countries in the post-drought period, which exactly replicate Australian productivity evolvement over the pre-drought period, as a "control group". The productivity of this counterfactual, the "drought-free" synthetic Australia, is then compared to that of the "actual" Australia to identify the impact of the Millennium drought.

This SCM, similar to the difference-in-differences approach, is most appropriate for the analysis of the productivity impact of Australia's Millennium drought as SCM is designed primarily to identify the causal impact of certain significant events, interventions or external shocks, occurred from some specific time period, on outcomes of a particular unit (i.e. country or region) that is of interest to researchers or policy makers. The Millennium drought affects Australia only, making it possible to identify its impact using information from Australia over the pre-drought period as well as that from other drought-free countries. Using SCM, we show that severe droughts occurred between 2002 and 2010 in Australia has brought down agricultural productivity by more than 20 percent over the period of 2002–2010, contributing significantly to the country's long-term slowdown of agricultural productivity growth. Our results highlight an important dimension – the productivity impact of extreme weather shocks - that has been overlooked when accessing the economic impact of climate change.

This paper contributes to the climate-economy literature in three ways. First, we investigate the economic impact of an *extreme weather* event, i.e., the Millennium drought, which affects Australia over the period 2002–2010. While a large body of literature studies the economic impact of changes in *average weather* (i.e. a one-degree increase in temperature or change in average precipitation), the impact of extreme weather events such as severe droughts arising from El Nino remains under-studied (Cashin et al., 2015; Rogoff, 2016), considering that vast small and young businesses are especially vulnerable to extreme weather (Collier, 2016). Second, it is well known that correct "identification" of the economic impact of climate change remains a key challenge as there are usually other covariates of climate variable such as farmers' spontaneous responses or particular institution arrangements may contaminate the estimation (Dell et al., 2012; Cashin et al., 2015). We depart from the existing literature by applying a recently developed technique, i.e., the synthetic control method (SCM thereafter), to construct a "counterfactual" which is not "treated" and thus are better equipped to identify the casual impact of such an extreme weather. Third and most important, unlike previous studies that focus on the contemporaneous economic impact as measured by the loss of current output or a fall in GDP per capita, we focus on the medium to long term productivity impact. Although several studies address one of the above three dimensions,[2] to the best of our knowledge, we are the first to examine climate-economy relationship through the lens of the above three dimensions combined.

There are several recent attempts to explore the impact of droughts on agricultural productivity. Alexander and Kokic (2005), Kokic et al. (2007) and Zhao et al. (2009) examine the farm-level agricultural productivity and its determinants in agricultural industries and show that droughts negatively affect agricultural productivity growth in the long run. Sheng et al. (2010) and Hughes et al. (2011)) use farm survey data to examine various drivers of agricultural productivity growth in Australian broadacre agriculture. Recently, Sheng et al. (2010) and Hughes et al. (2011) use aggregate and farm-level data respectively to re-examine the impacts of droughts and show that changes in average climate conditions reduce productivity over the post-2000 period. Among others, changing climate condition and stagnation of public R&D investment are identified as two important factors contributing to the productivity slow-down in Australian agriculture. However, most of these studies do not provide credible identification of the productivity impact of drought as compared with other factors such as R&D investment. Our study is also related to the literature that examines the economic impact of extreme weather condition. For example, Hanslow et al. (2014) examine the impact of changes in key climate variables, including "extreme" climate scenario, on pasture growth and hence on stocking rates and output in key dairy-producing regions in south-eastern Australia. Mukherjee et al. (2012) incorporate climatic indexes into the stochastic frontier framework to show that the significant nonlinear impact of heat stress on milk production efficiency for a sample of dairy farms from the south-eastern US. Yang (2008) finds that stronger storms results in higher output loss.

The remainder of the paper proceeds as follows. Section 2 describes the case of the Millennium Drought in 2000s and their impacts on

[1] In the case of drought, a few studies examine qualitatively and quantitatively its social and economic impact (White, 2000; Gornall et al., 2010; ABARE, 2012).

[2] For studies on extreme weather events, Yang (2008) finds that stronger storms results in higher output loss. For studies on long-run impact, Dell et al. (2012) examine *average weather events* and suggest that average temporary shocks have long-lasting effects.

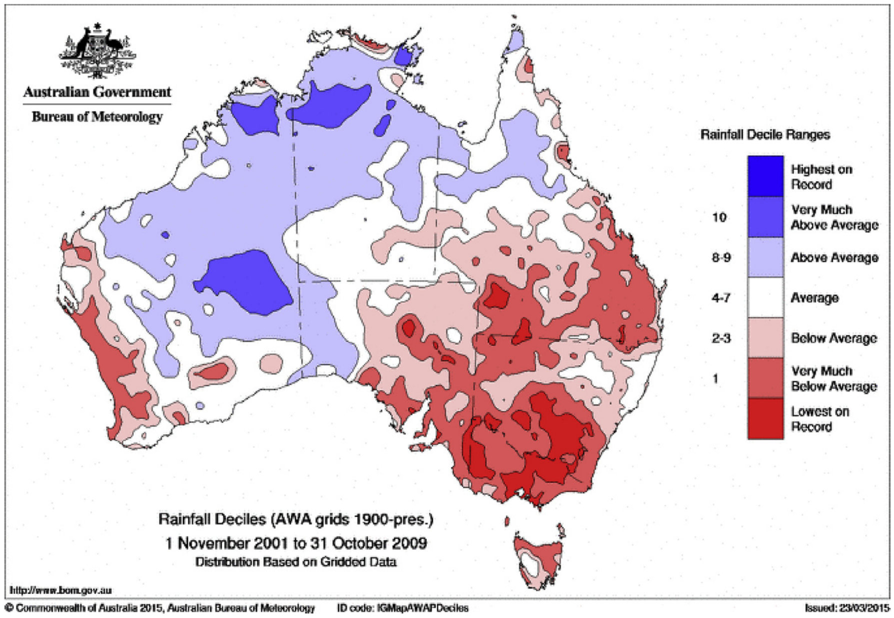

Fig. 1. Rainfall deciles for the period March 2002 to February 2003.
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Australian agriculture. Our empirical methodology in identifying the productivity impact of the Millennium Drought is described in Section 3. Section 4 presents data and variable definitions. Section 5 discusses the empirical results with robustness checks in Section 6. Section 7 concludes.

2. Australia's Millennium Drought

Drought in Australia is generally defined as precipitations over a three-month period being in the lowest decile of what has been recorded for that region in the past long-term (i.e. 20 years) record. This definition takes into account the fact that drought is a relative term of rainfall shortage or in other words, an abnormally dry period with insufficient rainfall water for users' normal needs (BoM, 2006). Compared to the rest of the world, Australia is more vulnerable to frequent and widespread droughts, and the country has recorded the lowest level and most variable rainfalls over the past century. Every two to seven years, *El Niño* events would severely reduce rainfall in winter and spring particularly across Eastern and Southern Australia, where the majority of cropping and livestock industries are located. In addition, droughts also occur locally without being related to *El Niño* events. There are, on record, at least 12 national wide droughts (namely, 1864–66, 1880–86, 1895–1903, 1911–16, 1918–20, 1939–45, 1963–68, 1972–73, 1982–83, 1994–95 and 2002–2007) taken place since 1860, and research indicates that most parts of Australia has on average suffered from droughts every other decade (BoM, 2011).

Although droughts cause damages to agricultural production, their impact on agricultural production could vary significantly. In practice, some droughts are long lived while others are short and intense. Given the high frequency of their occurrence, expected droughts have, to some extent, been taken into account by farmers and agribusinesses in their risk management. However, there are still "severe droughts" outside the scope of "normal" risk management that has a profound impact. Throughout the past century, the worst drought to affect the country occurred between the years 2002–2010, which is also known as the 'Millennium drought'.

Starting from late 2001, a series of prolonged and severe droughts (initially due to the typical life cycle of an El Niño event) hit the country. As a result, rainfall that was below normal was recorded for most of Australia from 2002 to 2003. Analysis of rainfall records showed that 90 percent of the continent received rainfall below the long term median for the 11-month period March 2002 to January 2003 (see Fig. 1), with 56 percent of the country in the lowest 10 percent of recorded totals (Watkins, 2003). The situation became even worse, when the second wave of droughts hit Eastern and Southern Australia in 2006. The average rainfall in South Australia by late 2006 set its lowest level record since 1900. Victoria and New South Wales reached the second and the third driest season since 1900 respectively. Worse still, the temperature in Australia reached the highest on record since the 1950s. Though there was a short break in 2008, drought conditions in Southeast Australia continued through 2009, being one of the driest summers for Victoria and New South Wales. It was not until early 2010 that droughts in major Eastern states (including Queensland, New South Wales and Victoria) started to ease.

The severity of this drought had caused economic disruption and individual hardship for majority of rural communities, as it led to significant decline in agricultural production and farmers' real income. For example, about 90 percent of New South Wales, 65 percent of Queensland and 48 of 59 municipalities in Victoria had been officially declared drought area by August 2003, and below average seasonal conditions were also affecting parts of South Australia, Tasmania, Western Australia and the Northern Territory (Lu and Hedley, 2004). Water use by agriculture fell by 37 percent between January 2000 and May 2004, due mainly to drought. As for costs of agricultural production, more than half had been consumed by the drought. Australia's farm gross domestic product fell by 24.8 percent in 2003 and 18 percent in 2006. Significant declines were also observed for rural exports and agricultural income for the years 2003 and 2006 respectively.

The Millennium drought reshapes the thoughts of Australian farmers, industrial organizations and government agencies about sustainable development of agriculture. Various public policies are implemented aiming at improving the forecasts on seasonal conditions, encouraging the use of more water efficient production technologies, minimizing economic and social costs of droughts and nurturing the ability to recover after droughts. For policy making and reforms, it is crucial to understand how severe drought may affect the capacity of production measured by agricultural total factor productivity.

3. Theoretical framework and empirical strategy

3.1. A simple theoretical framework

In modelling the climate-economy relationship, the literature typically incorporates climate factors such as temperature, precipitation and windstorm into an otherwise conventional Cobb-Douglas production function through a damage function (Dell et al., 2009, 2012; Barrios et al., 2010). Specifically, consider the production function $Y_t = (1 - D_t^c)A_t K_t^\alpha L_t^{1-\alpha}$, where Y_t, K_t, L_t, A_t denote output, capital, labor and total factor productivity (TFP) at time t respectively, $\alpha \in (0,1)$, and D_t^c is a damage function capturing the contemporaneous effects c of climate factors such as temperature, precipitation or both at year t. Under this specification, climate factors affect only the level of contemporaneous output. That is, it has only level effect but no growth effect as in the spirit of Solow (1956).

However, as discussed in the Introduction section, an emerging body of empirical evidence points to the fact that climate change, in particular extreme weather events, could have long-lasting effects on output, i.e., climate factors could have growth effects (Stern, 2013; Dietz and Stern, 2015). To capture the growth effects of extreme weather, we follow Dietz and Stern (2015) by considering an endogenous growth model where climate factors exert impacts on the long-run growth of TFP. Without lose of generality, we consider again the production function $Y_t = A_t K_t^\alpha L_t^{1-\alpha}$, where productivity A is affected, for example, by the speed and magnitude of farmers' adoption of new technology due to uncertainty or lack of confidence for future climatic condition. That is, climatic shocks affect TFP, which can be captured by the following equation of motion:

$$A_{t+1} = \left(1 - D_t^c\right)A_t. \tag{1}$$

Under this specification, climate factor such as a drop in precipitation at year t leads to contemporaneous falls in output through damage function D_t^c. However, a significant drop in precipitation, i.e., drought, has now an effect on TFP growth: it reduces TFP next year by (1-D_t^c). That damage persists by a factor of $(D_t^c)^n$ at the nth year in the future. This formulation has the advantage in that it captures not only the level effect of changes in precipitation but also growth effect that reduce TFP arising from severe drought. Although simple and transparent in theory, the mechanism through which severe drought affects agricultural TFP growth is much complex and hard to quantify empirically which calls for new strategy.

3.2. Identification: the SCM

Applying the above theoretical framework to quantify the impact of droughts on agricultural total factor productivity, the challenge is not to deal with the endogeneity problem but the identification problem. First, droughts affect agricultural TFP through a complex process. For example, a severe drought may change famers' choice on input mix in production or the efficiency of machinery/intermediate input use, which could also be affected by technological progress. Thus, the impact of droughts is confounded by other productivity determinants and could not be easily disentangled. Second, the degree of drought's severity, which usually changes over time, is very hard to measure at the national (aggregate) level. In particular, a single continuous variable such as temperature or precipitation, would provide a very imperfect picture of the severity of droughts that varies across region and over time. Consequently, using an inappropriate measure of drought's severity in conventional OLS regressions is likely to lead to biased estimates.

Similarly, other regression techniques such as panel data regression or dynamic panel regression, which may include dummy variables, interaction terms between climate variables, time trend, and other TFP determinants, do not help much in separating the impact of drought on agricultural TFP from other factors, since the drought impact is confounded with the impacts of these factors. Similar problem applies when using a difference-in-differences regression.

Different from regression analyses, the SCM proposes to use a sample of countries other than Australia over the pre-shock (or pre-drought) period to identify the contribution of various productivity predictors to agricultural TFP under no drought condition. Specifically, the SCM synthesizes a control from a weighted sum of donor regions chosen from a pool of potential candidates. That weighted sum is created by matching agricultural TFP and its underlying determinants in the pre-drought period of the donor regions with the same variables in the pre-drought period of Australia. Valid implementation of the SCM requires that the control's outcome closely matches the treated entity's outcome during pre-drought period. If the two match closely, comparing the outcome paths after the treatment provides insight about the drought impact. Thereafter, the SCM combines the estimates with the productivity predictors of "drought-free" countries to construct a "counterfactual Australia" over the post-drought period. If the outcome paths of the synthetic control and the treated entity are similar in the treatment period, the drought does not appear to have affected the outcome. However, if the paths diverge, the treatment presumably caused the difference.

It is worth highlighting three features of the SCM which distinguish the method from conventional regression methods. First, the SCM splits the observation period into the pre-shock period and the post-shock period, and uses the observations in the pre-shock period to form the parameter estimates. This unique research design allows us to identify the impact of the explanatory variables (other than drought) on TFP. Second, in the pre-shock period, the SCM does not use the regression-type method (i.e. OLS, panel data regression etc.) but focusing on estimating a set of weights to aggregate the selected donor regions. This is because the regression analysis uses the sample regions to retrieve a latent "actual" relationship between outcome variable and explanatory variables, which could be different from the relationship between outcome variable and explanatory variables in the target country (since the target region, e.g. Australia in our exercise, is only one of them). The goodness of fit of the model with the target region (not the latent relationship) gets worse the larger the number of donner regions behaving differently from the target region. Third, in the post-shock period, the SCM uses the information of donner regions with the estimated weights from the pre-shock period to construct the counterfactual. In contrast, regression methods use the explanatory variables from the target region in the projection. As the observed explanatory variables for the target region over the post-shock period could be contaminated by the shock, the estimated impact using regression methods could bias the estimates.

Finally, the SCM also differs from regression methods even though the later approaches may use similar procedures to retrieve the coefficients of proposed explanatory variables from regressions for the pre-shock period and to construct the counterfactual through extrapolation. Although regression methods may have the potential to provide a good fit of the model to time-series data, it may not fit well the trend change of TFP in target region (i.e. Australia) over the pre-shock period. More important, it does not identify the drought impact in the post-shock period, if drought shocks also lead to changes in explanatory variables of the target region.[3]

[3] As an alternative approach, one could use the annual average precipitation, the soil moisture index or Palmer Drought Severity Index (Palmer, 1965) as an indicator to identify the impact of drought on agricultural TFP in Australia. However, using this approach generally tends to underestimate the drought impact for two reasons. First, the average precipitation or the soil moisture are more likely to reflect the long-term change in water availability for agricultural production rather than capturing the full impact of drought as an adverse seasonal shock. Second, drought usually affect agricultural TFP through a complex process and it usually interacts with change in temperature and the timing of rainfall, which could not be captured by the average precipitation indices. To avoid the above two problems, we prefer to use the synthetic control approach.

3.3. Estimation of the SCM

Applying the SCM to examine the impact of the Millennium drought on agricultural productivity in Australia, we use observations of agricultural TFP at the industry level (an outcome variable) for a balanced panel of $N+1$ countries over T years, among which the first country is Australia. Australia (i.e. $n=1$) is the country of interest, and the other countries (i.e. $n=2, \ldots, N+1$) are potential comparisons (controlled countries in the donor pool). Let TFP_1 be a $\mathrm{T} \times 1$ vector of the values of agricultural total factor productivity for Australia during the period, and TFP_0 be a $\mathrm{T} \times \mathrm{N}$ matrix of those for the controlled countries. Moreover, the Millennium drought is treated as the significant event or intervention, which occurred in Australia since $T > \mathrm{T}_0$ (from 2002) but not in the other N countries. Thus, the first $\mathrm{T}_0 - 1$ years is defined as the pre-intervention period (when no significant drought has occurred) and $(\mathrm{T}_0, \ldots, \mathrm{T})$ is defined as the post intervention period.

Theoretically, agricultural TFP of Australia over the pre-drought period could be more accurately approximated by using a combination of controlled countries in the donor pool (or a synthetic control) than by any single controlled country (Abadie et al., 2015). To construct this synthetic control, we need to specify a group of weights such that $\mathrm{W} = (\mathrm{w}_1, \ldots, \mathrm{w}_\mathrm{N})'$ is a $N \times 1$ vector, where its component w_n $(0 \leq \mathrm{w}_\mathrm{n} \leq 1, \sum \mathrm{w}_\mathrm{n} = 1,\ 1 < n < N)$ represents the weight of country n in the synthetic control unit. However, choosing different weights would generate a different "synthetic" control unit.

Following Abadie et al. (2015), the basic principle for choosing a unique W^* among others is to approximate the productivity path of Australia in the absence of the Millennium drought, such that the path is as close as possible to that of the real agricultural productivity growth in Australia for the pre-intervention period (until T_0). Moreover, we know that industry-level agricultural TFP is determined by many characteristics other than the changing climate condition during the period under study. We can select W in a way that these non-climatic characteristics that determine agricultural productivity in Australia are best resembled by those non-climate characteristics of the synthetic control unit.

Specifically, let X_1 be a $\mathrm{K} \times 1$ vector of pre-drought characteristics for Australia that determine its agricultural productivity but has nothing to do with the changing climate condition (such as endowments in land, labor force, technology, and its past performance, etc.), and X_0 as a $K \times \mathrm{N}$ matrix of the values of those variables for the N countries in the donor pool. Let V be some $K \times \mathrm{K}$ symmetric positive semi-definite matrix. Both X_1 and X_0 refer to averages over the pre-drought period, since only their time averages over pre-shock years are used when creating the synthetic region. The optimal weights of controlled countries, W^*, is therefore chosen such that the distance function between the counterfactual synthetic control unit and Australia before droughts occurred is minimized:

$$\mathrm{W}^* = \underset{\mathrm{W}}{\operatorname{argmin}} \left\{ (\mathrm{X}_1 - \mathrm{X}_0\mathrm{W})' \mathrm{V} (\mathrm{X}_1 - \mathrm{X}_0\mathrm{W}) \right\} \tag{2}$$

where $\mathrm{V} = (\mathrm{v}_1, \ldots, \mathrm{v}_\mathrm{K})$ is a vector of initial weights that reflects the relative importance of the k-th variable when we measure the discrepancy between X_1 and $\mathrm{X}_0\mathrm{W}$. By default, the SCM can use the regression-based method to select this predictor weights. Alternatively, one can specify their own predictor weights. Note that in allocating V between different X s, one should give relatively higher weights to those variables with a larger predictive power so that the synthetic control could closely reproduce agricultural productivity pattern of Australia in the period before the Millennium drought.

Using the optimal weights obtained from (2), as long as those characteristics have a stable relationship with agricultural productivity in both the target region and the donor regions, the cumulative effect of drought α_t at year t $(\mathrm{t} > \mathrm{T}_0)$ can be calculated as

$$\alpha_\mathrm{t} = \mathrm{TFP}_1^\mathrm{t} - \mathrm{TFP}_0^\mathrm{t}\mathrm{W}^* \tag{3}$$

where $\mathrm{TFP}_1^\mathrm{t}$ and $\mathrm{TFP}_0^\mathrm{t}$ are the tth element of TFP_1 and TFP_0, respectively. In other words, for a post-drought period t (where $t \geq T_0$), the synthetic control estimator of the effect of the Millennium drought is given by the difference between the agricultural productivity in Australia affected by droughts, $\mathrm{TFP}_1^\mathrm{t}$, and the synthetic control which is unaffected by droughts for the same period of time, $\mathrm{TFP}_0^\mathrm{t}\mathrm{W}^*$. Note that the matching variables in X_0 and X_1 are predictors of post-drought period for controlled countries and the target country.

In principle, the SCM is an extension of comparative studies using the difference-in-differences (DID) approach. However, the SCM differs from the DID approach in that the later assumes that the unobserved effects are constant over time so that taking first difference eliminates these effects. In contrast, the SCM allows the presence of time-varying unobserved cofounding effects. Relative to large-sample based regression analysis, the SCM provides similar results with more significant advantages. First, the SCM uses a weighted average of controlled units as a "control group", which avoids extrapolation biases usually associated with regression results (King and Zheng, 2006). Second, the SCM offers a systematic way to choose and construct comparison units. This allows a more explicit analysis of the similarities and differences between the case of interest and the synthetic control, through identifying the relative contribution of each comparison unit to the synthetic control.

4. Data sources and variable definitions

We use the annual country-level panel data for the period 1961 to 2011. The sample period starts in 1961 since it is the first year that cross-country consistent estimates of agricultural TFP growth and their determinants are available. It ends in 2011 when Australian government ceased to provide the Federal 'exceptional circumstances' drought support in most regions.[4] Since the Millennium drought in Australia is identified at the late 2001 when the first round of drought assistances were provided by the Federal government, the dataset provides us with about 40 years of pre-intervention data and a decade-long period for predicting effects of the Millennium drought.

The synthetic Australia is constructed as a weighted average of potential comparison countries. The weights are chosen so that the resulting agricultural productivity of synthetic Australia should best reproduce realized agricultural productivity of Australia before the drought period. Since the synthetic Australia will be used as a counterfactual that would have been observed for Australia in the absence of droughts, it is important to restrict the donor pool to countries with agricultural productivity growth that are driven by the same structural process as Australia but did not experience similar droughts over the sample period. In particular, those potential comparison countries which had experienced significant changes in climate condition over the pre-intervention period should be excluded from the donor pool. Using this criteria, 45 countries have been chosen which include 22 OECD countries and some major developing countries from South America and Southeast Asia. These 45 countries are South Africa, Kenya, Malawi, Namibia, Mexico, Colombia, Peru, Brazil, Argentina, Chile, Uruguay, Canada, the United States, Japan, Republic of Korea, China, Indonesia, Laos, Malaysia, Thailand, Vietnam, Bangladesh, India, Nepal, Austria, Denmark, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, the United Kingdom, Cyprus, Malta, Switzerland, Egypt, Morocco, Israel, Turkey, Iran, Saudi Arabia and New Zealand. Finally, we also drop observations over four sub-periods (including 1963–1968, 1972–1973, 1982–1983 and 1991–1995) since droughts of different levels had also occurred over these sub-periods in Australia.

The outcome variable of interest is the logarithm of the level of

[4] On 27th April 2012, Australian agricultural minister, Joe Ludwig, formally declared the end of Millennium drought and ceased to provide 'exceptional circumstances' drought support for the last two areas, Bundarra and Eurobodalla in New South Wales (Howden, 2012).

agricultural total factor productivity (TFP) at the country-level, measured as the ratio of gross output to gross input. The estimates are derived by using data obtained from Fuglie and Rada (2013) where 1961 is defined as the base year. The estimates of agricultural TFP growth in Fuglie and Rada (2013) were made by using the annual Food and Agriculture Organization (FAO) statistics on agricultural outputs and inputs with the assumption of a Cobb-Douglas production function and fixed revenue and factor shares for individual countries.[5] Although these estimates use many imputed input cost shares as weights when data are not available, they are better, for the purpose of our study, than those obtained by applying a distance function (i.e. the Malmquist index) to data on output and input quantities only (Coelli and Rao, 2005). This is because agricultural TFP growth rates calculated based on distance function approach are more sensitive to aggregation issues and data quality, which typically leads to unstable estimates over time (Fuglie, 2012).

For predictors of agricultural TFP to be controlled for, we include standard variables in the literature which can be broadly classified into three categories: resource endowment, technology, and human capital broadly conceived to include education, skill, knowledge and capacity embodied in a country's population (Hayami and Ruttan, 1970, p. 895). These variables include output structure, the logarithm of total crop land areas, agricultural land use per capita, capital-labor ratio, the logarithm of total fertilizer used, the logarithm of literacy rates, the logarithm of secondary school enrolment ratio, population density, urbanization rate and the logarithm of GDP per capita. All these variables are chosen and defined following the literature on cross-country difference in agricultural productivity (Hayami and Ruttan, 1970; Ball et al., 2001, 2010). Meanwhile, we have also considered the disparity in economic development levels across countries to capture the differences in institutional arrangements and their implications for cross-country productivity differences (Adamopoulos and Restuccia, 2014, Gollin et al., 2014a,b).

We obtain data on controlled predictors from the World Bank World Development Indicator (WDI) database (World Bank, 2015). This World Bank WDI database provided information on macroeconomic development, institutional arrangements related to agricultural production and other natural and environmental constraints of each country at the national level. More than 15 variables are collected and compiled for 171 countries over the period of 1961–2011, which are used to construct factors (other than changing climate conditions) that could affect agricultural productivity growth across countries. We collect data on capital stock used in agriculture, land use and output structure from FAO statistics.

5. Empirical results

Measuring the drought effects on agricultural TFP in Australia is a challenging task as it is difficult to separate the effects that are due to the Millennium drought from others. Although the regression technique (including OLS, panel data regression and dynamic panel regression), the difference-in-differences approach and the synthetic control method could be used in estimation, the synthetic control method is preferred since it provides a more systematic way to construct a "drought-free" counterfactual. This section considers the estimated effect of the Millennium drought using the SCM and compares it with those obtained from other methods.

5.1. Results from synthetic control method

We first compare Australia's agricultural TFP index with that of the average 45 countries in the donor pool. As can be seen in Fig. 2, before

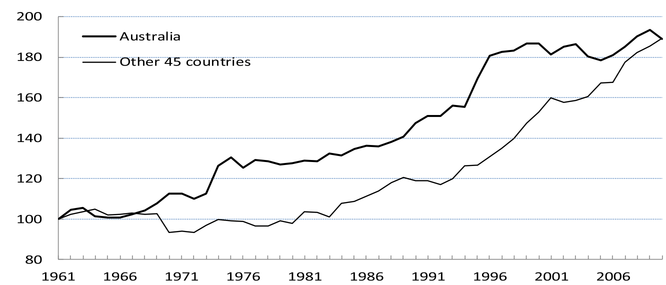


Fig. 2. The agricultural TFP in Australia and in countries in the donor pool: 1961–2011.
Source: Authors' estimates.

the drought occurs, the trend of agricultural TFP in Australia differed notably from that in other countries. In particular, agricultural TFP growth is significantly higher in Australia than that in the other 45 countries over the period 1970 to 2000. This suggests that a direct comparison of Australia's agricultural TFP index with that of the 45 countries in the donor pool would not provide much useful insights for the impact of the Millennium drought.

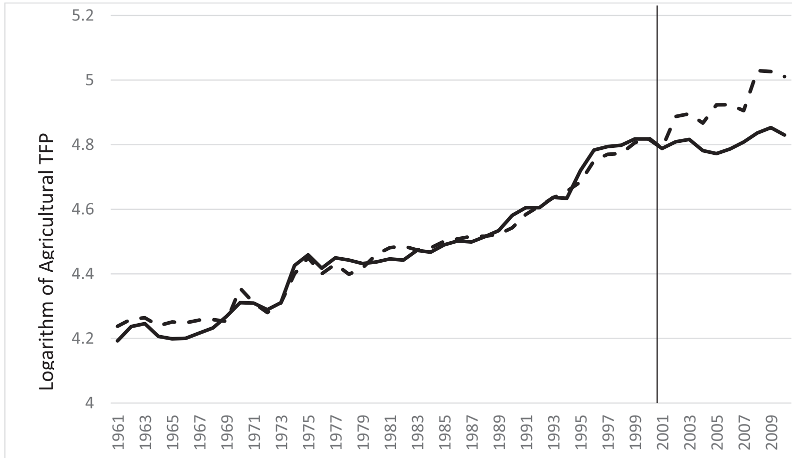
Applying the synthetic control method, we construct a counterfactual Australia as the convex combination of countries in the donor pool that most closely resembled Australia in terms of pre-drought values of agricultural TFP. The results from SCM indicate that the agricultural TFP level in Australia prior to the Millennium drought is best reproduced by a combination of only six countries: New Zealand (0.351), Argentina (0.291), the United States (0.145), Canada (0.127), Israel (0.072) and Denmark (0.014), with New Zealand obtaining the highest W-weights of 0.351. All other countries in the donor pool are assigned zero W-weights. This implies that only the six countries have played the most important role in constructing the synthetic Australia.

Fig. 3 compares the logarithm of agricultural TFP for Australia and its synthetic counterpart for the period 1961 to 2010. As can be seen, the *synthetic* agricultural TFP of Australia tracks closely with the trajectory of *real* agricultural TFP of Australia for the entire pre-drought period. The root mean squared prediction error (RMSPE), which is used to measure the fit between real and synthetic agricultural TFP, over the pre-drought period is 0.0423. This suggests that the synthetic Australia provides a reasonably good approximation to the trend of agricultural TFP that would be achieved in the absence of the Millennium drought.

However, since the Millennium drought occurred after 2001, the agricultural TFP between *synthetic* Australia and the *actual* Australia begin to diverge noticeably. While agricultural TFP in *synthetic* Australia continued on its growing trend, agricultural TFP in *actual* Australia experienced a significant slowdown. The difference between the two lines continue to widen until 2010 when the Millennium drought ends. For the period 2001 and 2010, the growth rate of agricultural TFP in actual Australia is 0.53 percent a year, compared with that in the synthetic Australia of 2.34 percent a year. The gap in agricultural TFP growth between the synthetic and actual Australia after 2001 suggests that the Millennium drought has imposed a substantial negative effects on agricultural TFP. The magnitude of the impact of the Millennium drought on agricultural TFP in Australia is large and persistent over time. Over the period between 2001 and 2010, Australia's agricultural TFP level has declined approximately by 18.2 percent.

Droughts impose negative impact on agricultural TFP growth through two channels. On the one hand, unexpected droughts will reduce outputs given unchanged inputs and thus lead to lower productivity. On the other hand, droughts may reduce profits and thus negatively affect farmers' confidence in adopting new technologies which reduce the efficiency of machinery and intermediate inputs. The former channel usually occurs in the short term while the latter channel is more likely to occur in the long term. In the case of Australia, the Millennium drought has generated

[5] Fuglie and Rada (2013) provides cross-country consistent estimates of agricultural TFP growth for 174 countries over the period of 1961–2011, which is one of the most widely used statistics in international comparison of agricultural TFP.



Note: The dash line refers to the agricultural TFP of the "synthetic" Australia while the solid line is that of the "actual" Australia. Source: Authors' estimates.

Fig. 3. Impact of the Millennium drought on agricultural TFP in Australia (in logarithm).

negative impact on agricultural TFP growth mainly through the latter channel. Negative effects of the Millennium drought are not only statistically significant but also economically meaningful in magnitude and long lasting.

We now briefly compare results from the synthetic control method and those from conventional regression methods such as simple OLS with the drought dummies, panel data regression with random effects and dynamic panel data regression with the control of one-period lag. As can be seen in Table 1, the impact of the Millennium drought on agricultural TFP estimated using different regression methods is negative with the magnitude rangeing from 2 per cent to 6.1 per cent, which is less than half of that obtained using the synthetic control method, i.e., 18 percent. Moreover, if we use various regression methods to fit the trend of agricultural TFP in Australia over the pre-drought period and construct the counterfactual Australia for the post-drought period, we can see that the counterfactual using the regression analysis is also much lower than the synthetic one (see Fig. 4). One possible reason of this difference is that the determinants underlying the agricultural TFP in Australia over the post-drought period could be interacted with and negatively affected by the Millennium drought. Even if the regression analysis may fit well with the trend of agricultural TFP over the pre-drought period as the SCM method, the constructed counterfactuals from estimates in the regression methods using the Australian predictors may have been contaminated by the Millennium drought leading to biased results.

To further explain the difference in the estimated effects of the Millennium drought obtained from the regression methods and those from the synthetic control method, we retrieve the corresponding weights used in the synthetic control method. Only 6 out of the 45 countries in the donor pool are specified to be relevant in constructing the synthetic Australia and are given weights in the synthetic control method. Since the weights for six countries (namely, New Zealand, Argentina, the United States, Canada, Israel and Denmark) are restricted to be positive and sum to one, this provides a safeguard against extrapolation over the post-drought period (Abadie et al., 2010, p. 494).

Table 1
Impact of the Millennium drought: OLS, panel data and dynamic panel regressions.

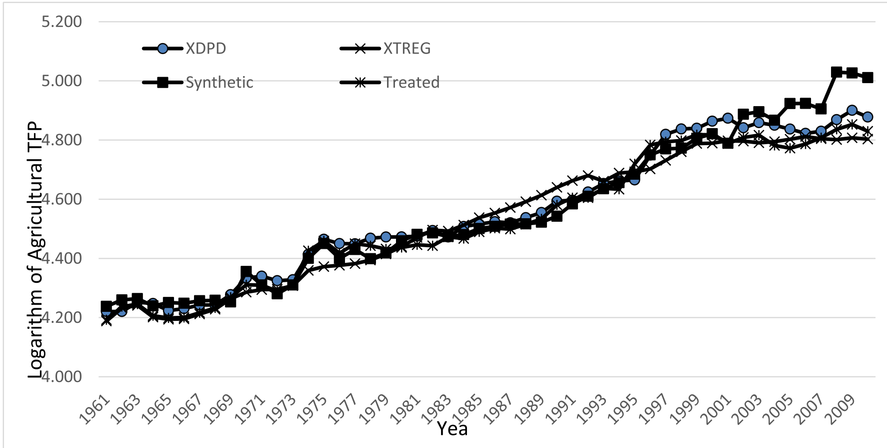
	OLS	Panel RE	Dynamic Panel
Dependent variable: ln_TFP			
drought_dummy	−0.061***	−0.020***	−0.024*
	(0.027)	(0.001)	(0.014)
logarithm of land per capita	0.054	0.125**	−0.149***
	(0.081)	(0.051)	(0.025)
capital-labor ratio	0.000***	−0.000	0.000***
	(0.000)	(0.000)	(0.000)
logarithm of fertilizer use per hector	−0.025	−0.016	−0.114***
	(0.037)	(0.024)	(0.004)
output mixture ratio	−0.162	−0.059	0.016
	(0.151)	(0.073)	(0.021)
enrollment rate of secondary schools	0.276***	−0.079**	0.036**
	(0.071)	(0.040)	(0.015)
population density (population per sq. km of land area)	0.161	0.000	0.002***
	(0.121)	(0.000)	(0.001)
urbanization rate	0.007**	−0.001	0.007
	(0.003)	(0.002)	(0.004)
logarithm of agricultural value added per capita	−0.029	−0.017	0.119***
	(0.071)	(0.017)	(0.023)
logarithm of population	0.152**	0.020	0.114
	(0.065)	(0.025)	(0.237)
one-period lagged variable	–	–	Yes
	–	–	Yes
constant	0.632	−34.76***	−0.499***
	(0.805)	(2.597)	(0.177)
Number of Observations	1409	1409	1409
Adjusted R2	0.694	0.469	–
F-statistics	–	–	112,206

Note: ***p < 0.01, **p < 0.05, *p < 0.1. "Panel RE" refers to panel data regression with random effects, and "Dynamic Panel" refers to dynamic panel data regression.

6. Robustness check

The SCM enables researchers to conduct a wide range of falsification exercises by allowing systematic estimation of the counterfactual of interest, which are termed as "placebo studies" (Abadie et al., 2015). In measuring effects of the Millennium drought on agricultural productivity in Australia, we carry out "placebo studies" to examine the robustness of our findings.

First, the Millennium drought is a unique external shock affecting agricultural production in Australia, but not elsewhere in the world. Thus, the estimated effects on agricultural productivity growth obtained from the synthetic control analysis should be specific to Australia and would disappear for other countries when such droughts are artificially reassigned to them (placebo test). This gives us a hypothesis that when applying the SCM to analyze agricultural productivity pattern of other controlled countries in the donor pool, the measured effects would be



Note: XDPD and XTREG refer to the trajectories derived from the dynamic panel regression and the panel data regression with random effects respectively.
Source: Authors' estimates.

Fig. 4. Comparison of drought impact between the SCM and alternative regression methods.
Source: Authors' estimates.

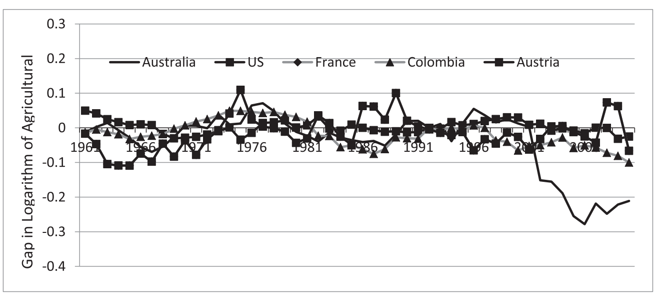


Fig. 5. Comparison between Australia and other placebos.
Source: Authors' estimates.

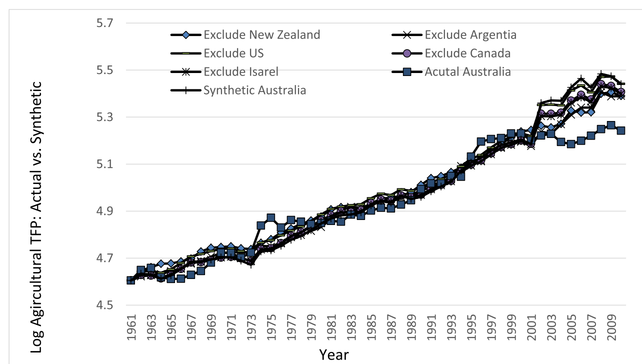


Fig. 6. Sensitivity test for 'leave-one-out' result.
Source: Authors' estimates.

fairly small from a statistical perspective. To test this hypothesis, we applied the SCM with the same setting to some random selected countries in the donor pool following Abadie and Gardeazabal (2003) and Abadie et al. (2010).

Fig. 5 presents the results for the placebo test. The grey lines represent the gap in logarithm of agricultural TFP between the placebo countries and their corresponding synthetic counterparts, while the black line denotes the gap estimated for Australia. The estimated gap for Australia during the drought period of 2002–2010 is unusually large relative to the gaps for other countries in the donor pool.[6] This implies that the synthetic control method provides a good fit for the agricultural TFP over the pre-drought and post-drought periods for most countries in the donor pool, which in turn lends support to the evidence of negative effects of the Millennium drought on Australian agricultural productivity.

Second, the SCM makes use of a linear combination of drought-free controlled countries with coefficients that sum to one to construct a synthetic control unit. Thus, the choice of weights W^* determines the similarity of the control unit to the unit representing the case of interest in terms of agricultural productivity growth and their determining characteristics, which in turn affects the appropriateness of comparisons and the accuracy of measurement. We can thus test the sensitivity of our results to the changes in the country weights, W^*. As it is discussed in previous section, the synthetic Australia is estimated as a weighted average of New Zealand, Argentina, the United States, Canada, Israel and Denmark, with weights decreasing in this order. Thus, we can iteratively re-estimate the baseline model by constructing a synthetic Australia that drops in each iteration one of these countries to check whether our results are sensitive to the exclusion of any particular sample country.

Fig. 6 compares the agricultural TFP of the synthetic Australia obtained from these placebos with that obtained from the initial synthetic Australia. The grey lines represent the leave-one-out estimates, while the black line denotes the initial synthetic Australia. Although there are some differences between those estimates, the estimates of initial synthetic Australia are generally consistent with those of the leave-one-out result. This implies that our analysis is fairly robust to the exclusion of any particular country form the comparison group.

Third, the Millennium drought has occurred to affect agricultural production after 2001 but we have observations of changing agricultural productivities and their determinants from 1961. Moreover, there are many minor droughts that occurred from time to time which break the whole pre-intervention period into several uneven sub-periods. Thus there may be concerns that the SCM captures the productivity effects specific to the period of the Millennium drought. To evaluate this concern, we use a new cross-validation technique developed by Abadie et al. (2010). Specifically, we first divide the pre-intervention period into a training period from 1961 to 1981 and a validation period from 1981 to 2001. We then use estimated predictors in the training period to choose

[6] In Abadie et al. (2010), another test also used to examine the relative magnitude of the pre-intervention is mean squared prediction errors (MSPE).

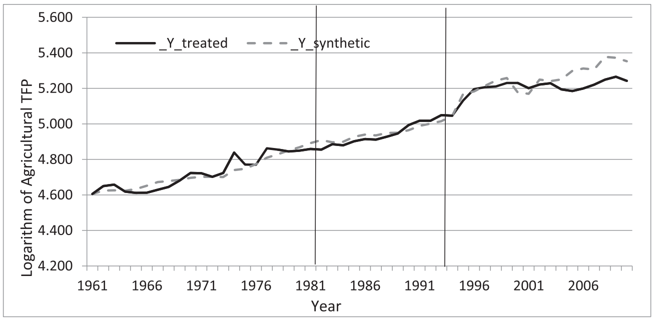


Fig. 7. Comparison of "in-time" placebos.
Source: Authors' estimates.

the weights V such that the resulting synthetic control minimizes the root mean square prediction error (RMSPE) over the validation period. Intuitively, the weights V are chosen to minimize out-of-sample prediction errors. Finally, we use the set of V weights selected in the previous step and predictor data measured in 1981–2001 to estimate a synthetic control for Australia. In both steps, the periods when minor droughts occurred are excluded from the analysis for the training and validation periods. Intuitively, we compare the drought effect estimated for Australia to a placebo effect obtained from reassigning the Millennium drought to the early 1980s and the early 1990s when minor droughts had also taken place. If we find similar or larger estimated effects than the one estimated for the period after 2002, we would be less confident that the effect estimated for the Millennium droughts is attributed to droughts.

Fig. 7 displays the results of these two "in-time placebo" studies. Still, the grey line represents the placebos, while the black line denotes the initial synthetic Australia. In both placebo scenarios, the synthetic Australia almost exactly reproduces the evolution of agricultural TFP in the actual Australia for the pre-intervention period. More importantly, the trend of agricultural TFP in Australia and its synthetic counterpart do not diverge considerably during the period before 2001. Compared to the initial scenario in which the Millennium drought actually took place in 2002, these results imply that the 'in-time' placebo has no perceivable effects — a supportive evidence for predictive power of the synthetic control method in predicting the drought effects.

Finally, to evaluate the sensitivity of our results to predictors of agricultural TFP, we also include additional variables such as the proportion of cropping land areas in total agricultural land usage, the population density and the proportion of agricultural value-added in GDP in the analysis. The results are consistent with our initial estimates.

7. Conclusion

The impact of climate change has received rapidly increasing attention, involving not only researchers of various disciplines and policy makers worldwide but more importantly, the public. Until recently, the evaluation of the impact of climate change has been limited to estimating the short term output loss. Little is known as to its impact on the medium to long-term productivity. Taking Australia's Millennium drought as a case study, we illustrate that the impact of climate change on agricultural productivity both in the short and long runs, much higher than what has been estimated using conventional regression method by researchers and far beyond what the actual short term output loss suggests.

Specifically, we use the synthetic control method, combined with cross-country consistent measure, to examine the impact of the Millennium drought which is very hard to quantify — a crucial ecological shock to farmers — on agricultural TFP in Australia between 2002 and 2010. We are able to credibly identify the productivity impact of the Millennium drought as the synthetic control method constructs a "counterfactual" by using the selected "drought-free" countries similar as Australia for comparison. Our results show that the Millennium drought has on average reduced agricultural TFP by around 18 percent compared with a scenario that there is no such a severe drought. The estimated magnitude of drought effects in this study is two times as much as that obtained from using the conventional regression method with the same sample. Since the synthetic control method provides a better identification condition to net out the drought impact, it suggests that previous studies using regression analysis is likely to underestimate the negative effects of droughts.

More importantly, the substantial impact of climate change on the medium and long term productivity that we illustrate in this paper calls for more research as well as the attention of policy makers worldwide. If the true impact of various climate changes is substantial and long lasting as suggested by this study, the policy responses should not be the same as what if it is limited to short term output losses only.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.econmod.2018.07.031.

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